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Abstract

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Keywords

Age, estimation, based, extended, non, negative, matrix, factorization

Disciplines

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Age Estimation Based on Extended Non-negative Matrix Factorization

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Abstract—Previous studies suggested that local appearance-based methods are more efficient than geometric-based and holistic methods for age estimation. This is mainly due to the fact that age information are usually encoded by the local features such as wrinkles and skin texture on the forehead or at the eye corners. However, the variations of these features caused by other factors such as identity, expression, pose and lighting may be larger than that caused by aging. Thus, one of the key challenges of age estimation lies in constructing a feature space that could successfully recovers age information while ignoring other sources of variations. In this paper, non-negative matrix factorization (NMF) is extended to learn a localized non-overlapping subspace representation for age estimation. To emphasize the appearance variation in aging, one individual extended NMF subspace is learned for each age or age group. The age or age group of a given face image is then estimated based on its reconstruction error after being projected into the learned age subspaces. Furthermore, a coarse to fine scheme is employed for exact age estimation, so that the age is estimated within the pre-classified age groups. Cross-database tests are conducted using FG-NET and MORPH databases to evaluate the proposed method. Experimental results have demonstrated the efficacy of the method.

I. INTRODUCTION

Automatic face analysis has been an active research topic over the last 20 years. To mimic the amazing ability of human face perception, computer vision and pattern recognition researchers have made great efforts to extract different kinds of information from facial images (videos), including identity, gender, pose and expression. However, relatively few studies have been conducted on age estimation. One of the key reasons for this situation is that the personalized and uncontrolled aging process makes age estimation a challenging task even for human beings. Another reason is that large aging databases are hard to collect. Recently, with the release of public aging databases (MORPH [1], FG-NET[2]) and attractive potential applications such as demographics, supervision of minors, customer group analysis and album management, increasing number of techniques are being investigated to achieve a reliable age estimation [3].

Existing methods for age estimation either label an input face image automatically with the exact age or the age group

of the face. The exact age estimation is often treated as a regression problem, while the age group estimation can be formulated as a pattern classification problem. Although intuitively it seems that age group classification could be easier, majority of the existing works attempt to estimate exact age based on regression techniques. This is mainly due to that aging is a continuous progress and age groups do not have clear borders. Therefore, no matter how the age groups are divided, it is always hard to make correct classification for border ages. However, in real applications, sometimes the age group information is more meaningful than the exact age of a person. We naturally classify a person into baby, child, young adult or senior adult and always describe a unknown person's age using age groups. Although the estimated exact age can be transformed into corresponding age group by simply binning, without utilizing the age group information properly during training process, the accuracy of this "transformed" age group estimation could be very low [4]. In this paper, we handle the age estimation as a classification problem and consider both exact age estimation and age group classification.

Early works for age estimation use geometric (anthropometric) features to extract age information from face images. These geometric-based methods utilize the location of facial landmarks such as the eye corners, mouth corners, and nose tip to determine age from their distance ratios [5], [6]. Obviously, the geometric-based methods are sensitive to accurate localization of the facial points and only work for frontal face images. Furthermore, the shape of human faces do not change too much during adult aging, thus without considering the texture information, geometric-based methods may work for young ages but are not appropriate for adults.

By modeling the face with both shape and texture information, active appearance model (AAM) has shown its efficiency in many applications and is also widely used as the face representation for age estimation. Lanitis et al. [7] proposed a quadratic aging function that maps the AAM features of a face image to an age. The authors also compared different classifiers for age estimation based on AAM features in their later work [8]. With AAM based face encoding, Geng et al. [9], [4] handled the age estimation problem by introducing an aging pattern subspace (AGES), which is a subspace representation of a sequence of individual aging face images.

The problem of AAM based representation for age estimation is that AAM only encodes the image intensities without using any spatial neighborhood to calculate texture patterns. Intensities of single pixels usually cannot characterize local texture information [3]. However, many studies suggested that age features are usually encoded by the local information, such as wrinkles and skin texture on the forehead or at the eye corners. The same problem also exists in other holistic methods such as subspace methods ([10]) and Gabor wavelet based methods ([11], [12]).

In order to extract the local information, local descriptors such as LBP [13] and spatially flexible patch (SFP, that integrates coordinate information together with the local DCT feature) [14] are applied in age estimation. The extracted features could successfully encode the shape and texture information of local facial areas. However, an important consideration is the fact that the face appearance contains all kinds of information, feature variations caused by other factors such as identity, expression, pose and lighting may be larger than that caused by aging. Thus, one of the key challenges of age estimation lies in constructing a feature space that could successfully recover age information while ignoring other sources of image variation.

In this paper, non-negative matrix factorization (NMF) is extended to learn a localized non-overlapping subspace representation for age estimation. To emphasize the appearance variation due to aging, one individual extended NMF subspace is learned for each age or age group. The age or age group of a given face image is then estimated based on its reconstruction error after being projected into the learned age subspaces. Furthermore, a coarse to fine scheme is employed for exact age estimation, so that the age is estimated within the pre-classified age groups. During the coarse to fine scheme, to alleviate error propagation caused by misclassifying border ages, additional border age groups are introduced for the top-level age group classification.

The rest of the paper is organized as follows: In Section II a brief introduction is given on nonnegative matrix factorization and its major extensions. Detail of the proposed method is described in Section III. Section IV presents the implementation of the proposed methods and the experimental results. Conclusions are drawn in Section V.

II. NONNEGATIVE MATRIX FACTORIZATION

Non-negative matrix factorization (NMF) [15] is a linear, non-negative approximate data representation. Given a non-negative data matrix $V = (v_{ij})_{m \times n}$, NMF finds the non-negative matrix $W = (w_{ij})_{m \times r}$, and the non-negative matrix $H = (h_{ij})_{r \times n}$, such that $V \approx WH$. The rank r of the factorization is generally chosen to satisfy $(n+m)r < mn$, so that the product WH can be regarded as a compressed form of the data in V . Let V represents a face database, each column of V contains n pixel values of one of the m face images in the database. Then, each face in V can be represented by a linear combination of r columns of W , the columns are called basis vectors (images). Each column of H is called a coefficient vector, that is in one-to-one correspondence with

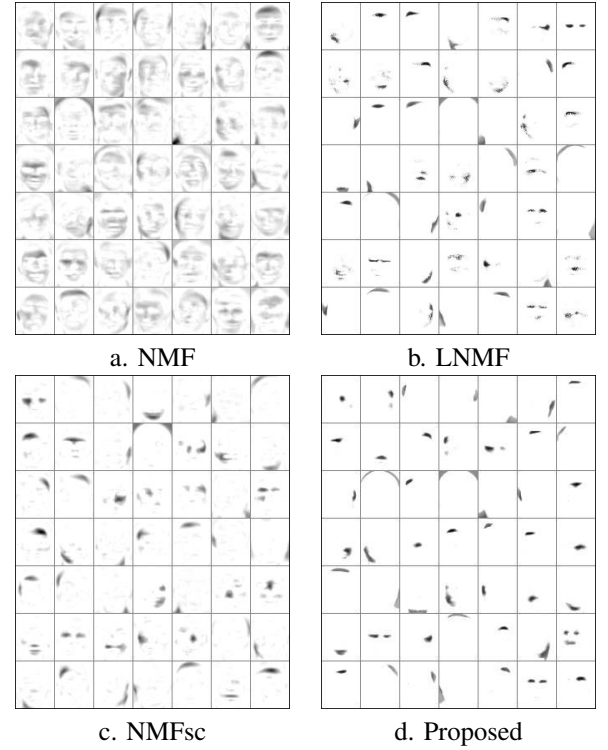


Fig. 1. Basis images learned from ORL database using different methods ($r = 49$).

a face in V and describes how strongly each basis is present in the face. Since entries in W and H are all non-negative, only additive combinations of the basis vectors are allowed. Thus, NMF naturally leads to a part-based representation, the learned basis images tend to match intuitive facial features like mouth, nose and eyes.

NMF can be taken as an optimization problem, where W and H are chosen to minimize the reconstruction error between V and WH . Various error functions (objective functions) have been proposed, a widely used one is the Euclidean distance function:

$$E(W, H) = \|V - WH\|^2 = \sum_{i,j} (V_{ij} - (WH)_{ij})^2 \quad (1)$$

Although the minimization problem is convex in W and H separately, it is not convex in both simultaneously. Paatero and Tapper [16] proposed a gradient decent method for the optimization, Lee and Seung [17] devised a multiplicative algorithm to reach a local optimum.

One of the issues of NMF is that it does not always give a part-based representation. As suggested by Li et al. [18], when NMF is applied on ORL face database [19], in which faces are not well aligned, the learned basis images are holistic rather than local part-based (as can be seen in Figure 1a, the results are reproduced by us). To improve the performance of NMF in learning part-based representation, Li et al. proposed a local NMF method (LNMF) [18], that adds three additional

constraints on NMF: Maximum Sparsity in H , Maximum Expressiveness of W , Maximum Orthogonality of W . Figure 1b shows the basis images learned from ORL database using LNMF. Comparing with NMF, we see that features gained by LNMF are more localized. However, some of the bases are still global and overlapped with each other. Furthermore, since more constraints are imposed, the convergence of LNMF is time consuming.

As an effect of part-based decomposition, NMF usually produces sparse representation. W is sparse since the learned bases tend to be non-global. H is often sparse due to that any given sample does not consist of all the available parts (bases). Hoyer [20] proposed a method called NMF with sparseness constraints (NMFsc), and suggested that by explicitly controlling the sparseness of W and H , NMF could give a more meaningful part-based representation. In NMFsc, the level of sparseness is measured based on the relationship between the L_1 norm and the L_2 norm:

$$\text{sparseness}(\mathbf{x}) = \frac{\sqrt{n} - (\sum |x_i|) / \sqrt{\sum x_i^2}}{\sqrt{n} - 1} \quad (2)$$

where n is the dimensionality of \mathbf{x} . Then NMFsc is defined as the following optimization problem:

$$\begin{aligned} \min_{W, H} E(W, H) \quad s.t. \quad & W, H \geq 0, \sum_i W_{ij} = 1 \quad \forall j \\ & \text{sparseness}(w_j) = S_w, \forall j, \\ & \text{sparseness}(h_j) = S_h, \forall j \end{aligned}$$

where w_j is the j th column of W and h_j is the j th row of H ; S_w and S_h are the desired sparsenesses of W and H respectively. We show the basis images learned from ORL database using NMFsc in Figure 1c, where S_w is set to 0.75 and S_h is unconstrained as the best result achieved in [20]. As can be seen from the figure, NMFsc does not give a better part-based representation than LNMF. However, directly controlling the sparseness of the representation is very useful for many applications.

III. THE PROPOSED METHOD

A. Extended NMF

In the proposed method, we extend the NMF for producing a localized, non-overlapping subspace representation. Inspired by LNMF and NMFsc, our extended NMF (ENMF) impose orthogonality constraint on basis matrix W while controlling the sparseness of coefficient matrix H . To reduce the overlapping between basis images, different bases should be as orthogonal as possible so as to minimize the redundancy. Denote $U = W^T W$, the orthogonality constraint can be imposed by minimizing $\sum_{i,j,i \neq j} U_{i,j}$. As introduced in Section II, for learning localized bases, LNMF adds two more constraints to maximize the sparsity in H . Maximum sparsity in the coefficient matrix makes sure that a basis component cannot be further decomposed into more components, thus the overlapping between basis images is further reduced. However,

a high sparseness in H forces each coefficient try to represent more of the image, and then the basis images tend to be global. Consider the extreme case when only one element in each column of H is allowed to be nonzero, then the NMF reduces to vector quantization (VQ), and all the basis images turn to holistic prototypical faces. Therefore, we chose to explicitly control the sparseness level of H , so that a compromise can be made between localization and overlapping and the value of the sparseness could be set based on different application scenarios.

The objective function of the ENMF is defined as:

$$E(W, H) = \frac{1}{2} \sum_{i,j} (V_{ij} - (WH)_{ij})^2 + \beta \sum_{i,j,i \neq j} U_{i,j} \quad (3)$$

where $U = W^T W$, β is a small positive constant. Then the ENMF is defined as following optimization problem:

$$\begin{aligned} \min_{W, H} E(W, H) \quad s.t. \quad & W, H \geq 0, \sum_i W_{ij} = 1 \quad \forall j \\ & \text{sparseness}(h_j) = S_h, \forall j \end{aligned} \quad (4)$$

where h_j is the j th row of H ; S_h are the desired sparsenesses of H ; the sparseness is measured based on formula (2). A local solution to the above minimization can be found by using the following two step update rules:

1)

$$W_{i\alpha} \leftarrow W_{i\alpha} \frac{(VH^T)_{i\alpha}}{(WHH^T)_{i\alpha} + \beta \sum_i W_{i\alpha}} \quad (5)$$

2)

$$H_{\alpha\mu} \leftarrow H_{\alpha\mu} - \mu_H [W^T (WH - V)]_{\alpha\mu} \quad (6)$$

Then project each row of H to be non-negative, have unit L_2 norm, and L_1 norm set to achieve desired sparseness S_h . (μ_H is a small positive constant. For the projection method, please refer to [20].)

Figure 1d shows an example of the bases learned from ORL database using the proposed ENMF, S_h is set to 0.1. As can be seen from the figure, more localized, less overlapped basis images are obtained, and limited bases contribute to each specific local facial area.

B. Age group classification

Let $V^{(k)}$ represents a set of face images that are all with one particular age group k , then a ENMF subspace $W^{(k)}$ learned from $V^{(k)}$ can be regarded as a specific feature space for the age group k . Given a new sample face image S (same size as the face images in the training set), its coefficient vector $L^{(k)}$ in the learned age group subspace $W^{(k)}$ can be obtained by:

$$L^{(k)} = W^{(k)-1} S \quad (7)$$

where $W^{(k)-1}$ is the pseudo inverse matrix of $W^{(k)}$. Based on the obtained coefficient vector $L^{(k)}$, the sample S can be reconstructed by:

$$S^{(k)} = W^{(k)}L^{(k)} \quad (8)$$

The reconstruction error $\epsilon^{(k)}$ between S and $S^{(k)}$ reflects the similarity between the sample and the training images that are with the same age group k , smaller value of $\epsilon^{(k)}$ indicates a higher probability that the age group of S is k . Thus, after ENMF subspaces are learned for each of the age group, the q th age group will be assigned to the given sample S , if

$$\epsilon^{(q)} = \min\{\epsilon^{(k)}\}(k = 1, \dots, p) \quad (9)$$

where p is the total number of age groups, and the reconstruction error is calculated by mean square error (MSE):

$$\epsilon^{(k)} = MSE(S, S^{(k)}) = \frac{1}{n} \sum_{i,j} (S_{ij} - S_{ij}^{(k)})^2 \quad (10)$$

where n is the number of pixel in the face image.

C. Exact age estimation

Following the observation that facial aging is perceived differently in different age groups, a coarse to fine scheme is employed for exact age estimation, so that the fine age is estimated from the pre-classified age groups. It has been proved that hierarchical classification scheme generally provides better performance than single-level classification especially for age estimation [8]. However, a problem with the hierarchical scheme is that the errors occurring in the top-level would be propagated to the sub-level. This problem is crucial for age estimation, since border ages tend to be misclassified into neighbor groups. To reduce the propagated errors, besides regularly partitioned age groups, additional border age groups that are set around the boundary of two adjoining age groups are used during the top-level age group classification, and then the sub-level age estimation is conducted within one selected regular age group as well as one selected border group (as shown in Figure 2). In particular, after ENMF subspaces are learned for each age group and each specific age, the exact age of a given face image S is estimated according to following steps:

- 1) Project S into each of the regular age group subspaces, select one regular age group with minimum reconstruction error.
- 2) Project S into each of the border age group subspaces, select one border age group with minimum reconstruction error.
- 3) Project S into each of the specific age subspaces within the range of selected age groups, find the age with minimum reconstruction error.

IV. EXPERIMENTAL RESULTS

A. Experimental setup

Two well-known, publicly available aging databases: FG-NET [2] and MORPH [1] databases are used in the experiments. The FG-NET database contains 1002 face images of 82 multiple-race subjects with large variation of lighting, pose,

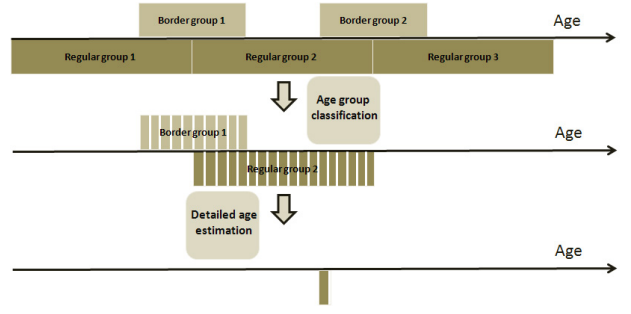


Fig. 2. The coarse to fine scheme for exact age estimation

Age group	MORPH (Album 2)	FGNET
0-9	0%	37%
10-19	13%	33%
20-29	29%	14%
30-39	28%	8%
40-49	22%	5%
50-59	7%	2%
60-69	1%	1%

TABLE I
AGE GROUP DISTRIBUTION OF THE IMAGES IN MORPH AND FG-NET DATABASE

and expression. For each image in the database, the location of 68 facial landmarks were obtained through manual annotation and are supplied with the database. There are two albums of face images in the MORPH database, only the second album is used in our experiments. Album 2 of MORPH database contains 55,134 images of 13,000 individuals collected over four years with applicable meta data for race, gender, date of birth, and date of acquisition. Table I shows age group distribution of the images in the two databases. As can be seen in the table, the age distribution of both databases is highly uneven. The album 2 of MORPH database does not contain face images younger than 16, very limited data are available for ages older than 50 in both databases.

In the experiments, images are converted to grey-scale and rotated so that the centers of eyes and mouth are at the same pixel coordinates in all images. Then the face area is cropped and resized to a final 64×64 face image.

B. Age group classification

The proposed age group classification method is tested using the FG-NET database with different age group partition schemes. In the first experiment, we only consider the age range of 0-44 and divide ages into 5 groups: 0-5 (preschool age), 6-11 (primary school age), 12-17 (secondary school age), 18-29 (young adult) and 30-44 (middle age). Images from 50 randomly selected subjects in FG-NET database are used as training set and data from the rest 32 subjects are all used for testing. For each of the age group, 90 images are selected from the training set to learn the corresponding age group subspace.

While fixing the number of basis r to 81, the proposed method is first tested with different value of S_h (the sparseness of coefficient matrix). The results are shown in Figure 3. We

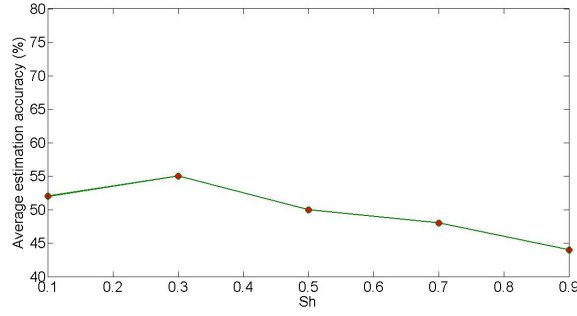


Fig. 3. The testing results for different value of S_h while r is fixed to 81

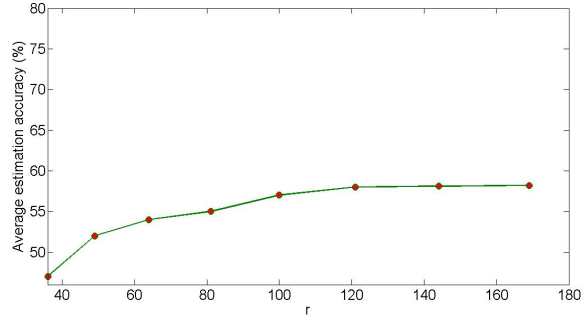


Fig. 4. The testing results for different value of r while S_h is fixed to 0.3

can see that the best result is achieved neither with the highest nor with the lowest sparseness, but when S_h is set to 0.3. This observation justifies our analysis in Section III-A, and demonstrates that a compromise made between localization and overlapping improves the efficiency of NMF for age representation.

Then, we set the value of S_h to 0.3 and test the proposed method by changing the number of basis r . The results are shown in Figure 4. As can be seen from the figure, higher estimation accuracy are obtained as the number basis increases. However, the increase is limited especially when the value of r exceeds 121, in those cases almost the same results are obtained. For the rest experiments in this paper, we all set r to 121 and S_h to 0.3.

As introduced above, compared with exact age estimation, limited existing works explore age group classification based on benchmark databases. One of the works is [21], in which Kriegel employs AAM features and SVM classifiers to analyze different properties of faces. The FG-NET database is divided into 4 age groups: 0-19, 20-29, 30-39 and 40-69 for the age group estimation test. The author also conducts 2 age group classification by separating the FG-NET database at the age thresholds of 10, 14, 18, 20 and 30. In the second experiment, we compare the proposed method with Kriegel's work using the same experimental setup. The testing results together with estimation accuracies of the AAM+SVM based method reported in [21] are listed in Table II and Table III. As can be seen from the table, by focusing on the local information and characterizing different age group by a subspace respectively,

Age Group	AAM+SVM	Proposed
0-19	71.7%	84.6%
20-29	40.7%	49.7%
30-39	45.8%	51.1%
40-69	50.0%	58.2%
Overall	52.1%	60.9%

TABLE II
THE CLASSIFICATION ACCURACY FOR 4 AGE GROUP ESTIMATION

Age Threshold	AAM+SVM	Proposed
10	75.9%	87.1%
14	73.2%	85.9%
18	72.2%	85.3%
20	71.5%	84.0%
30	76.0%	86.3%

TABLE III
THE CLASSIFICATION ACCURACY FOR 2 AGE GROUP ESTIMATIONS

the proposed method achieves better results in all the cases especially for the young age group.

Based on the FG-NET database, Geng et al. [4] evaluated the performance of their AGES age estimator as well as Lanitis et al.'s AAS [8] and WAS [7] methods in age group classification. Following the experimental setup in [4], the proposed method is compared with AGES, AAS and WAS. In particular, ages from 0 to 69 are divided into 14 age groups, each of which contains 5 continuous ages, i.e. 0-4, 5-9, ..., 65-69. Since the number of face images for ages older than 44 in FG-NET is too small to learn ENMF subspaces, these images are all used for testing and the proposed method is trained using selected data from MORPH database for age groups in the range 45-69. As for ages of 0-44, four folds cross validation is performed on FG-NET. The average classification accuracy of the proposed methods as well as the performances of AGES, WAS and AAS reported in [4] are shown in Table IV. To illustrate the efficiency of the proposed ENMF representation, traditional NMF, LNMF and NMFsc are used to learn age group subspaces under the proposed framework for age group classification, the testing results are also included in Table IV. As can be seen in the table, our method achieves the best result and all the methods under the proposed framework outperform the rest works. Especially, all our results are obtained by four folds cross validation and cross-database test, that is more challenging than Leave-One-Person-Out (LOPO) strategy used in [4] for testing AGES, AAS and WAS.

C. Exact age estimation

The performance of proposed coarse to fine age estimator is evaluated based on cross-database test. Due to lack of sufficient data, we only consider the age range of 15-59. For each age from 15 to 59, 90 face images (mainly faces of white people) are selected from MORPH database album 2 as training data to learn ENMF subspaces of different specific ages and age groups. For the coarse age group classification, 5 regular age groups (15-23, 24-32, 33-41, 42-50, 51-59), and

Method	Accuracy
AGES	40.92%
WAS	18.16%
AAS	26.65%
NMF	42.37%
LNMF	44.16%
NMFsc	41.24%
ENMF	45.77%

TABLE IV
THE CLASSIFICATION ACCURACY FOR 14 AGE GROUP ESTIMATIONS

Age	ENMF	ENMF'	BIF [12]	AGES [9]	RUN [22]
10-19	3.21	3.59	3.39	3.83	3.76
20-29	7.46	8.15	4.30	8.01	6.38
30-39	13.23	17.46	8.24	17.91	12.51
40-49	17.17	25.96	14.98	25.26	20.09
50-59	18.83	25.21	20.49	36.40	28.07

TABLE V
THE MAE FOR EXACT AGE ESTIMATION, ENMF' DENOTE THE PROPOSED METHOD WITHOUT USING BORDER GROUPS

4 border age groups (21-26, 30-35, 39-44, 48-53) are used. All images within the considered age range from FG-NET database are used as testing samples. In order to justify the introduction of border age groups, the proposed method is also tested by only using regular age groups during the age group classification level. The performance is measured by mean absolute error (MAE), which is defined as the average of the absolute errors between the estimated ages and the ground truth ages. The obtained results are compared with reported results of the state-of-the-art in age estimation. We show the results for different age ranges in Table V; ENMF' denote the proposed method without using border groups. MAEs of other works are all testing results based on FG-NET database using LOPO strategy. As can be seen from the table, with the more challenging cross-database test, the proposed method still achieved the best result for age range 10-19 and 50-59. For other ages, our method is competitive and sometimes superior to competing approaches. By using additional border age groups during top level age group classification to reduce the propagated errors, we can see that the performance of the proposed method is highly improved.

V. CONCLUSION

In this paper, non-negative matrix factorization (NMF) is extended to learn a localized non-overlapping subspace representation for age estimation. To emphasize the appearance variation in different ages, one individual extended NMF subspace is learned for each age or age group. The age or age group of a given face image is then estimated based on its reconstruction error after being projected into the learned age subspaces. Experiments based on the benchmark aging database demonstrate that the proposed facial representation can be effective for age estimation. For future work, the ENMF based representation could be employed in other face related applications such as face recognition and expression recognition.

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